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THE USE OF ARTIFICIAL INTELLIGENCE METHODS IN THE INTELLIGENT DECISION SUPPORT SYSTEM

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Abstract—*The article is devoted to the study of the use of artificial intelligence methods in decision-making support systems, particularly in military affairs. Examples of the application of artificial intelligence methods, such as expert systems and machine learning, which can be used to optimize management and strategic decisions in military operations, are considered. Special attention is paid to the use of decision trees in military scenarios as a tool for modeling possible options for the development of events and making optimal decisions. Decision trees allow a decision support system to analyze possible courses of action based on different conditions and circumstances. The results of the study emphasize the importance of using artificial intelligence to improve the efficiency and quality of decision-making in military affairs.*

Index Terms—Intelligent decision support system; artificial intelligence; decision tree; operations research.

I. INTRODUCTION

When studying management processes in various spheres of activity – public administration, business, emergency situations, medicine and military affairs – it turns out that the problem of uncertainty, lack of complete information and its distortion is one of the biggest challenges facing science. For example, when choosing an action strategy in business, uncertainty may lie in changes in legislation, in the market or technological shifts. In military affairs, when choosing a variant of the method of using troops, the uncertainty lies in the incompleteness of the data on the composition of the enemy's forces and means, as well as in the probable nature of his actions.

When making decisions, the decision-maker uses his experience, subjective views on the importance of various criteria and factors that influence alternative options. These aspects may be limited by the knowledge and experience of the decision maker, which in turn may lead to bias or incomplete consideration of all possible options. In addition, the importance of criteria and factors may be perceived differently depending on the situation and context, which may lead to different results when making a decision based on subjective evaluations.

Based on the fact that with the increase of data that influence decision-making, there is a need to use algorithms and artificial intelligence methods that allow efficient processing of large volumes of data, to perform analysis taking into account many factors, which increases the accuracy and quality of decisions. The development and implementation of intelligent decision-making support systems using artificial intelligence methods is a necessity in connection with the growth of the volume of data and the complexity of management tasks.

In military affairs, intelligent decision support systems using artificial intelligence methods will contribute to increasing the efficiency of resource use, reducing risks and reducing losses. They are necessary for quick and informed decision-making at the strategic, operational and tactical levels.

The task is to develop requirements for the system, the basis of which will be the methods of artificial intelligence, which will ensure the optimal use of military resources and the maximization of the effectiveness of the decisions made in conditions of uncertainty and dynamic changes in the situation on the battlefield. The main task of the system is to analyze the situation on the battlefield, including the location of one's troops and the enemy's troops, assessment of potential threats and combat capabilities, as well as determination of optimal actions to achieve tactical, operational and strategic goals. The system must be able to quickly respond to changes in the situation and provide recommendations to the command for decision-making. To do this, it must be able to process large volumes of data, take into account the uncertainty and risks of hostilities, as well as ensure confidentiality.

II. THEORETICAL ASPECTS OF INTELLIGENT DECISION SUPPORT SYSTEMS

The functioning of intelligent decision support systems can be described as a process of constant analysis of current situations to achieve a certain

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goal (Fig. 1). Important steps in this process may include:

- perception of initial information about the situation: the system receives information about the surrounding world, which allows it to form an initial description of the situation;
- comparison of knowledge with external description: the system compares the received information with its own knowledge, criteria for evaluating alternatives and forms a secondary description in the form of several options;
- comparison of knowledge with external description: the system compares the received information with its own knowledge, criteria for evaluating alternatives and forms a secondary description in the form of several options;
- reverse interpretation of the decision: the algorithm of the system's response to the decision is formed.

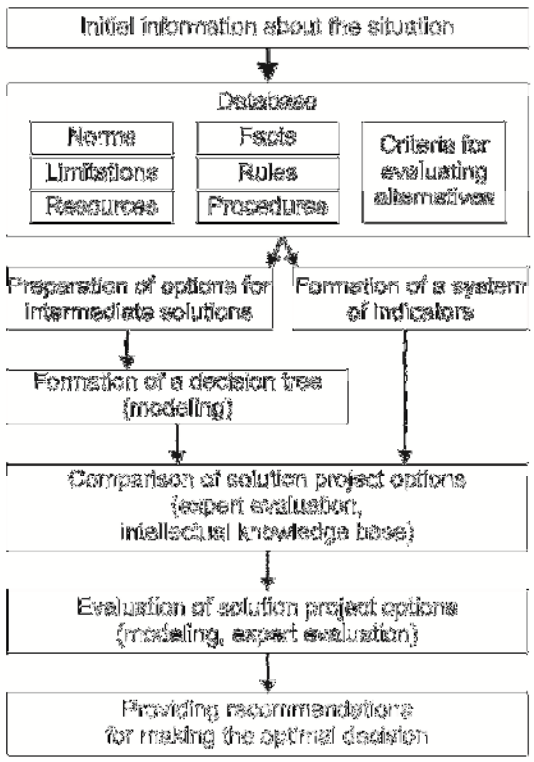


Fig. 1. Scheme of functioning of the intelligent decision support system

The theoretical foundations of intelligent decision-making systems are based on the ideas of decision-making theory, which studies the processes of choosing the optimal option among alternatives. One of the key concepts is the decision-making model, which includes defining goals, identifying alternatives, evaluating each alternative, and choosing the optimal one. An important element of the theory is also the consideration of uncertainty and risk that may arise when making decisions in real conditions of complexity, limitations and uncertainty.

Artificial intelligence methods can be used in intelligent decision-making support systems, which are an important tool for analyzing and optimizing decision-making processes. For example, expert systems based on the knowledge of experts help to analyze the situation and draw informed conclusions, while machine learning allows systems to adapt to new conditions and make predictions based on the analysis of large volumes of data.

Neural networks allow modeling complex relationships between data, and genetic algorithms help in finding optimal solutions in complex spaces of possible options. These techniques can be used individually or in combination to create intelligent systems that help solve complex problems and management tasks, providing more accurate and efficient decision-making results.

III. Methodology of Using Artificial Intelligence Methods in Intelligent Decision Support Systems

The functioning of any intellectual system consists in the perception of the external situation and the reaction to it. After analyzing the situation, the system makes a decision on the choice of action, taking into account its goal. However, this is only the final stage of the planning process. Action planning includes the analysis of all possible actions and their consequences. The system evaluates the possible consequences and chooses the action that is most beneficial for achieving the expected result.

A wide class of decision-making problems can be formulated as a classic optimization problem: to find a solution in which the objective function reaches a maximum under the set constraints. For example, the manager of a firm wants to maximize profits by obeying the law. Or you need to land a spaceship on Mars as soon as possible, but taking into account the limitations on the force of the impact.

Similar tasks are the subject of operations research [1], [2], [3]. More formally, the optimization problem can be formulated as follows:

find $x = (x_1, \ldots, x_n)$, *for which the function* $f(x)$ *reaches its maximum and the constraints* $g_i(x) \geq 0$ *are satisfied.*

Function $f(x)$ is *the target function*, and functions $g_i(x)$ – are *the constraints* of the optimization problem.

Any element x that satisfies the constraint $g_i(x) \geq 0$ is an admissible solution to the problem. At the same time, if there is no condition for finding an extremum, then this is the task of finding admissible solutions, and if there are no restrictions, then it is about unconditional optimization.

The type of objective function and the type of constraint functions affect partial cases of optimization problems, each of which has its own solution methods.

Along with the classical ideas of optimization, the ideas of successive analysis of options, selection of the best options and successive narrowing of the set of possible solutions are developing.

Among the methods of solving optimization problems, there is a universal method - the method of complete sorting, which consists in sorting through all possible options. But it can be applied in the case of a finite set of solutions. At the same time, for most practical situations, the number of options is too large and it is not considered possible to implement the specified method in an acceptable time.

Due to the fact that in most situations it will be enough to limit yourself to a solution that is close to the optimal one in an acceptable time, it is possible to apply algorithms that would exclude a complete enumeration of intermediate situations.

In such cases, appropriate rules are used that allow to reduce such a search.

Many practical tasks can be solved with the help of heuristic search, which is a systematic method of sorting, based on a consistent analysis of possible options and an assessment of their consequences. According to [4], the general scheme of heuristic search can be presented in the following form:

- choosing an action from a set of possible actions based on appropriate calculations;
- perform an action that leads to a change in the situation;
- assess the new situation;
- if success is achieved, then complete, if not, return to the first step and start again.

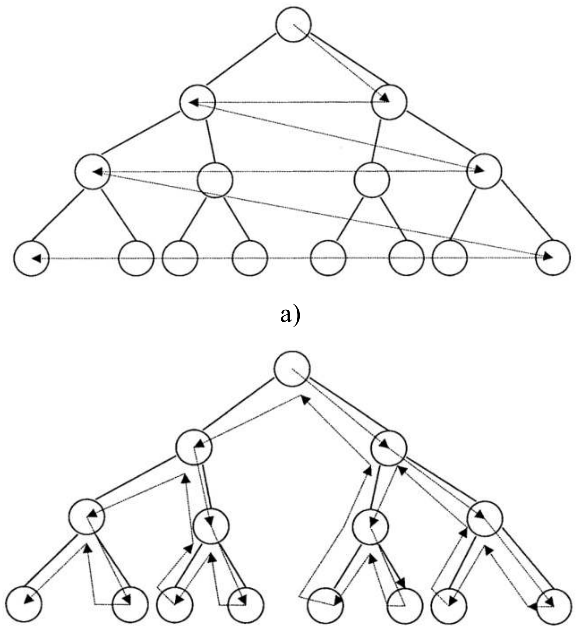
The action can be performed actually (in the case of a “trial and error” strategy) or imagined (in the case of preliminary planning that precedes the actual decision-making).

One of the important methods of heuristic search is the method of successive improvements. Its basic idea is that if we have some approximation to the solution x^k, we use some procedure to move to another approximation x^{k+1}, that is better than the previous one. Most of the main methods of operations research are based on the idea of the method of continuous improvement.

It is important to note that not all sorting algorithms are exponential. For example, we can mention the well-known algorithm for finding the largest element in an array. Although this algorithm is iterative, it is linear rather than exponential.

As the dimension increases, any polynomial algorithm becomes more efficient than any exponential algorithm. For example, for a linear algorithm, a 10-fold increase in the speed of the computer allows you to solve the problem in the same time, if its size increases by 10 times. In the case of the base-2 exponential algorithm, the 10-fold increase in size occurs only by adding 3 units.

Among the methods of organizing the search for the necessary vertex on the search tree and determining the path to it, two main strategies are distinguished (Fig. 2): breadth-first search and depth-first search (also known as search with returns or backtracking).



a)

b)

Fig. 2. Schematic representation of search procedures: (a) in width; (b) in depth

During the breadth-first search procedure, each next level of vertices that are directly connected to the vertices of the previous level that have already been visited is analyzed. This means that at each step, all possible options are studied at the same time (in the context of decision-making - a parallel check of all possible alternatives).

The depth-first search procedure first involves analyzing the descendants of the vertices that have just been visited. This means that all alternatives are considered in turn; the analysis of each alternative is completed only after it is determined whether it leads to success. If the alternative does not give a result, there is a return and consideration of other alternatives.

There are several examples where a depth-first search can be more efficient than a breadth-first search, and vice versa. In general, depth-first search saves memory because the entire search tree does not need to be stored in memory; it is sufficient to store only those vertices related to the current alternative.

In practice, the depth-finding procedure has become more widespread. It can be argued that iterating with return became a classic general intellectual procedure that formed the basis of modern methods of planning purposeful actions, programming games, etc.

Methods of planning purposeful actions can be divided into two classes [5]: planning in the space of states and planning in the space of tasks. When planning in the space of states, it is assumed that there is a certain set of states (situations). Actions that can be performed by the system and that determine the transition from one state to another are known. The state graph of the problem is called a directed graph, where the vertices correspond to the possible states of the domain, and the arcs indicate the methods of transition from one state to another.

Arcs can be marked with labels that reflect the cost or length of the transition. Thus, the solution to the problem consists in finding a path from the initial state to the goal state, often requiring optimization, for example, finding the shortest path. After the problem is formulated in the form of a formal model, it is possible to use various algorithms for finding paths on graphs, such as Moore's, Dijkstra's, branch-and-boundary algorithms, and others. A classic example of planning in the state space can be considered the problem of finding a way from one city to another.

Planning in the space of problems involves decomposition of the initial problem into subproblems until a reduction to problems for which there are ready-made solution algorithms is achieved.

Such search trees for use during decision-making in military affairs will be very large, since the options for the course of events are immeasurable. Therefore, to avoid a complete search of the tree, special procedures are introduced that allow viewing not all possible extensions to the constructed part of the tree, but only some of them and to a fixed depth [8].

The main challenge in this context is the determination of options for continuing movement along the search tree and the necessary depth of review to obtain a predictable assessment of the possible course of events in the future. For this, it is necessary to apply ranking with the accuracy and taking into account the given depth of calculations, which would allow to make an intermediate decision.

During each subsequent calculation of possible options for the development of events, taking into account the situation, state and position of one's troops and the enemy's troops, a knowledge base is formed based on the relevant indicators and optimality of the decision taken and the current stage. Among all the options in the knowledge base, the most optimal and effective solutions are highlighted - priority options for the development of events, which are subsequently used to reduce the time for searching for solutions or to increase the depth of the tree view. In the future, if for the current situation there is a priority variant of the development of events that will lead to the defeat of the enemy or inflicting critical losses on him, a sufficiently deep analysis and calculation of this variant is carried out. If the goal of the operation is achieved, this option will have the highest priority, will be implemented by the system and worked out as recommendations. If there are no priority options, the system will analyze the tree of possible actions, starting from the current position, five steps ahead, and choose its next action.

IV. LIMITATION OF THE DEPTH OF HEURISTIC SOLUTION SEARCH TREE

Let us denote the maximum depth of search as d. We will consider the horizon for a given position to be the set of positions whose distance to the root of the analysis tree of the subtree is exactly equal to the search depth. Thus, the analysis of the option should be completed upon reaching the horizon, i.e. depth d. However, not all positions that complete the truncated tree are on the horizon.

This is due to the fact that the drawing of options can be terminated earlier (for example, one of the parties can achieve its goals in the operation or has suffered critical losses that do not allow further execution of the specified tasks). On the other hand, positions that are definitely on the horizon are usually not final for the full parsing tree, but may turn out to be. In this regard, it seems appropriate to introduce the concepts of absolutely final and relatively final positions [6].

Absolutely final are the positions in which the draw of options ends, that is, those that are final for the full analysis tree. Positions that are final for a shortened tree, but not for a full tree, are called relatively final. All relatively final positions are generally assumed to lie on the horizon unless otherwise noted. The main problem with the depth-of-traversal limit is that for relatively final positions on the horizon, where the analysis of options from the current top ends, the valuation of the position is not yet determined. Therefore, static evaluation functions are used for these positions.

Static evaluation functions can be determined taking into account the specifics of a specific situation. This process is based on preliminary analysis, but in some cases one can hope for an automated selection of static evaluation functions.

Typically, linear static evaluation functions calculated according to the following formula are used:

$$S(P) = \sum_{i=1}^{n} a_i x_i,$$

where x_i, $i = 1, \ldots, n$ are the numerical values of the factors that influence the evaluation of the position; a_i, $i = 1, \ldots, n$ are weighting factors that determine the degree of importance of each factor.

The definition of a static evaluation function is simple and intuitive. But it is not completely clear, since the minimax assessment of the position is ultimately uniquely determined by this position. The main difference is that static estimates do not take into account the dynamics of the position, and therefore they are called static.

A minimax evaluation function is called a function $f : M \to R$, where M is the set of positions calculated using the minimax procedure and defined as the minimax score for each position.

A static evaluation function is called a function $g : S \to R$, where S is a set of positions, which is calculated based on the characteristics of the position itself and is defined as a static estimate for each position.

If we introduce a restriction on the search depth into the minimax procedure, this allows us to reformulate the procedure as follows:

1) the minimax estimate for absolutely final positions is equal to the profit function, while for conditionally final positions it is equal to the static estimate;

2) the evaluation of the alpha vertex in the minimax tree is defined as the maximum of the minimax evaluations of its immediate successors, which indicates the best move from the alpha vertex;

3) the evaluation of the beta vertex in the minimax tree is defined as the minimum of the minimax evaluations of its immediate successors, which indicates the best move from the beta vertex.

Therefore, the minimax procedure applied to a pruned tree allows finding the optimal strategy for this pruned tree only. The system should analyze only options that do not go beyond the horizon (ie, that do not exceed the maximum depth). For example, in a quite probable situation, in which one of the parties achieves the goal of the operation from the "optimal" node. If the search depth were to be increased by at least one move, the system would be able to see it and choose a completely different option. Therefore, the depth of the search is one of the decisive factors that determines the capacity of the system.

V. Conclusions

The use of artificial intelligence methods in intelligent decision-making systems opens up wide opportunities for optimizing management and decision-making processes in various fields of activity, including in the military sphere. This will allow to analyze the situation on the battlefield in real time, quickly react to changes, optimize the use of resources and reduce risks during decision-making. The implementation of such a system can significantly improve the quality of decisions made and reduce the level of losses during military operations, especially in the conditions of a large amount of data and the complexity of the scenarios of the development of events.

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В. І. Челкован. Застосування методів штучного інтелекту в інтелектуальній системі підтримки прийняття рішень

Статтю присвячено дослідженню застосування методів штучного інтелекту в системах підтримки прийняття рішень зокрема у військовій справі. Розглядаються приклади застосування методів штучного інтелекту, таких як експертні системи та машинне навчання, які можуть бути використані для оптимізації управлінських та стратегічних рішень у військових операціях. Особливу увагу приділено застосуванню дерев рішень у військових сценаріях як інструменту для моделювання можливих варіантів розвитку подій та прийняття оптимальних рішень. Дерева рішень дозволяють системі підтримки прийняття рішень аналізувати можливі варіанти дій на основі різних умов та обставин. Результати дослідження підкреслюють важливість використання штучного інтелекту для підвищення ефективності та якості прийняття рішень у військовій справі.
Ключові слова: інтелектуальна система підтримки прийняття рішень; штучний інтелект; дерево рішень; дослідження операцій.

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